Parameter drifts, misspecification and the real exchange rate in emerging countries☆

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A B S T R A C T

This paper reviews the baseline framework for the analysis of emerging economies. Using Argentinean data, I estimate a small open economy model with stochastic trend, working capital constraint and augmented with time-varying parameters. I find that "structural" technological and financial parameters of one-sector model are time-varying during 1936–2006. Time-varying parameters correlate with the real exchange rate, suggesting potential misspecification of the one-sector model. Therefore, I propose a two-sector model that endogenously accounts for the real exchange rate. In this model, stationary productivity shocks and the country premium together explain a large share of the variability observed in the data.

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1. Introduction

The business cycle in emerging markets differs from the business cycle in developed economies. The emerging markets' business cycle tends to be more volatile than that of developed economies; consumption volatility tends to be larger than the volatility of output; and the trade balance to output ratio tends to be strongly countercyclical. Conversely, developed economies exhibit consumption smoothing and acyclical trade balance to output ratio.[1] There is no agreement, however, on the theoretical framework with which to rationalize these facts. Influential articles, such as Kydland and Zarazaga (2003) and Bergoeing et al. (2002), study the dynamics of emerging markets driven by stationary technology shocks.[2] Other authors, alternatively, highlight the importance of non-stationary shocks or explicitly introduce frictions to the standard open economy real business cycle model.[3]

The objective of this paper is to review the basic theoretical framework for the analysis of emerging economies, i.e. to review the role of the one-sector real business cycle model as a baseline specification when studying emerging economies. To pursue this objective, I estimate a real business cycle model with stochastic trend, working capital constraint and time-varying parameters using annual Argentinean data for the period 1936–2006. I find that the data favor the model with time-varying parameters when compared to the standard business cycle model with trend shocks and working capital constraints. Then, I use the evidence from the time-varying parameters to identify potential

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[1] Aguiar and Gopinath (2007) and Neumeyer and Perri (2005) present a detailed study of business cycle facts for a large number of developed and emerging small open economies.

[2] Kydland and Zarazaga (2003) study Argentina's recent macroeconomic behavior and find that real business cycle models appropriately describe its business cycle up to a puzzle regarding the lack of investment recovery in the 1990s. On the other hand, Bergoeing et al. (2002) implement a growth accounting strategy in an open economy real business cycle model to describe the behavior of Mexico and Chile during the so called "lost decade".

[3] For example, Aguiar and Gopinath (2007) present a model with stationary technology shocks and permanent shocks and conclude that the volatility of the trend shocks is the key difference between developed and emerging economies, i.e., it is larger for emerging markets than for developed small open economies, inducing the facts observed in the data. In contrast, Boz et al. (2008) arrive at different conclusions following an alternate estimation strategy and argue that the trend shocks' volatilities in developing small open economies and developed small open economies do not differ from each other. Instead, different dynamics are due to informational frictions. Garcia-Cicco et al. (2010) reinforce the idea that standard real business cycle models with trend shocks might not be an appropriate representation of emerging economies using a large sample of annual data for Argentina. In turn, Neumeyer and Perri (2005) highlight the importance of working capital constraints and interest rate shocks to generate the observed facts and to rationalize the way real interest rates correlate with output and other macroeconomic variables.

sources of misspecification. I find that the time-varying parameters tend to change in times of large real exchange rate corrections. This leads to significant correlation between time-varying parameters and the real exchange rate. To check the robustness of this result, I replicate this exercise using Chilean and Mexican data for the period 1961–2012 with similar findings.

The economics behind the strong co-movement between real exchange rate and time-varying parameters goes as follows. During periods of crisis, the real exchange rate depreciates dramatically. In a model in which the real exchange rate is not modeled, this is captured by a change in parameters associated to the financial frictions this economy faces, i.e. financial parameters; and also by technological parameters that regulate the capital and labor shares and the intensity of capital utilization. Hence, I interpret this as evidence towards the misspecification of the one-sector real business cycle model. For this reason, in the rest of the article I develop and estimate a small open economy model with tradable and non-tradable sectors. I find that the two-sector model is able to explain a large share of the variability of national account variables and the real exchange rate once this variable is included in the vector of observables. I find that stationary productivity shocks and the country premium together, account for a large share of the variability observed in the dataset. This implies that these shocks are key driving forces in emerging economies. On the other hand, permanent technology shocks explain about one third of output and consumption volatility and have a mild impact in generating the variability of other observables. One important implication of this analysis is that the share of variability explained by the trend shock is remarkably different between the two-sector and the one-sector model. In other words, considering the endogenous variability of the real exchange rate highlights the role of transitory technology shocks compared to the permanent shock as a driving force of the business cycle in emerging economies.

The main contribution of this paper relies on the fact that the one-sector model is currently the baseline model to analyze macroeconomic behavior in emerging economies. For instance, Neumeyer and Perri (2005) and Uribe and Yue (2006) use the one-sector model to study the role of working capital constraints and interest rate shocks in emerging markets. Aguiar and Gopinath (2007) used a variant of this model to explore the effects of permanent and transitory technology shocks, while Garcia-Cicco et al. (2010)review these questions and use the one-sector model to highlight the importance of financial frictions and Boz et al. (2008) follow a similar strategy to study a linear Bayesian learning channel for the transmission of technology shocks. Hence, if the real exchange rate is important for the business cycle in emerging markets, several of the findings in the existing literature should be re-evaluated as these shocks and mechanisms in the existing literature do not consider this endogenous channel that implies sectoral, tradable and non-tradable, relocation.

My paper builds over the baseline one-sector model that includes many recently developed devices such as trend shocks and working capital constraints.[4] In addition to these features, my model allows for time-varying parameters. Therefore, this paper is also related to a growing literature on the estimation of models with parameter instabilities. Cogley and Sargent (2005), Sims (1999) and Primiceri (2005) estimate vector autoregression models with coefficient instabilities and time-varying volatilities for the US to study monetary policy during the Great Moderation, while King (2006), Justiniano and Primiceri (2008) and Fernández-Villaverde and Rubio-Ramirez (2007), among others, estimate dynamic stochastic general equilibrium models with parameter instabilities to study similar questions from a general equilibrium approach.

In this paper, I assume time-varying parameters follow autoregressive processes of order one, as in Fernández-Villaverde and Rubio-Ramirez (2007). Also in line with these authors, I assume that volatilities of the exogenous shocks are time-invariant. As pointed out by Sims (2001), this might be an important assumption. I work under this assumption because the estimation of nonlinear models using full information methods is still under study.[5]

This paper is also related to the study of the real exchange rates in small open economies and their importance as a transmission mechanism of foreign shocks, as in Mendoza (1995). Recently, the interest in the behavior of real exchange rate has increased. Mendoza (2005) studies the interaction between real exchange rate and sudden stops, Burstein et al. (2005) study the dynamics of the real exchange rate after large devaluations, Burstein et al. (2006) study the impact of changes in non-traded goods and the real exchange rate, while Burstein et al. (2007) study the role of sticky prices in non-traded goods sector. More recently, Aguirre (2011) studies the behavior of real exchange rate with shocks to the country spread and Ouyang and Rajan (2013) decompose the real exchange rate behavior of 50 economies over the last 20 years. However, the strategy in my paper is to extract information about the real exchange rate using national account variables through the lens of the one-sector real business cycle small open economy model with time-varying parameters that act as "wedges" that accommodate accordingly to the information contained in the data.

The remainder of the paper proceeds as follows: in Section 2, I discuss the benchmark one-sector model and the time-varying parameters assumption. In Section 3, I review the solution and estimation procedures used in this study and discuss the main estimation results. Section 4, studies the features of time-varying parameters and technology shocks in the time-varying parameters model and provides evidence supporting the misspecification hypothesis. Section 5 introduces and estimates a two-sector model. Section 6 provides concluding remarks and discusses directions for future research.

2. Small open economy model with parameter drifts

This section discusses the baseline one-sector model which builds on Aguiar and Gopinath (2007), Garcia-Cicco et al. (2010) and Neumeyer and Perri (2005) augmented with parameter drifts. In the following, I present the optimization problems of the firms and the households, and then, I introduce the stochastic processes of the time-varying parameters.[6]

2.1. Firms

I assume firms operate in competitive factors and goods markets. They rent capital and labor from households and combine them using a Cobb–Douglas technology to produce a unique type of good that can be traded internationally, used for investment or consumed. I follow Neumeyer and Perri (2005) and Uribe and Yue (2006) in assuming that firms need to advance a share of the total wages before starting the production process at any period t. However, while these authors assume that producers must always advance a fixed share of the total wages, I allow for the possibility that these shares could be time-varying.

The second key assumption regarding the firms' setup is that firms are subject to both transitory and permanent productivity shocks as discussed by Aguiar and Gopinath (2007) and Garcia-Cicco

[4] The online appendix replicates the time-varying parameter analysis of this paper taking as a baseline specification the financial frictions model in Garcia-Cicco et al. (2010). Even in this case, the behavior of time-varying parameters is similar to the one shown in Section 4.

[5] A recent paper, Andreasen (2013), reviews the features and caveats of nonlinear Bayesian estimation using a particle filter.

[6] I follow the convention in Garcia-Cicco et al. (2010). I use capital letters to denote variables in levels and lowercase letters to denote stationarized variables. A full set of equilibrium conditions for this model is available in the online appendix.

et al. (2010). The profit maximization problem of the firm is, hence, given by

$$\max \ \Pi = Q_t - \kappa_t(R_t - 1)W_t h_t - W_t h_t - R_t^k K_t.$$

where, $Q_t = A_t K_t^{\alpha_t}(X_t h_t)^{1-\alpha_t}$. Here, A_t denotes the stationary productivity shock that follows a mean reverting AR(1) stochastic process

$$\log A_t = (1-\rho_a)\log A + \rho_a \log A_{t-1} + \epsilon_{a,t}.$$

and X_t is the level of labor augmenting technology that grows at the rate g_t and follows a mean reverting AR(1) process,

$$\frac{X_t}{X_{t-1}} = g_t,$$
$$\log g_t = \left(1-\rho_g\right)\log g + \rho_g \log g_{t-1} + \epsilon_t^g.$$

I assume that innovations to these shocks follow a normal distribution, with $\epsilon_t^a \sim N(0, \sigma^a)$ and $\epsilon_t^g \sim N(0, \sigma^g)$. Importantly, as seen from the production function, I allow the capital share to be time-varying.

2.2. Households

Assume the economy is populated by households that maximize the present discounted value of expected utility. Households consume a unique consumption good C_t, rent labor h_t, and capital K_t to the firm, and are able to lend or borrow D_t in international markets at an interest rate R_t, which is exogenously given to the domestic economy. Given this setup, we can formalize the households' optimization problem as follows:

$$\max \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(C_t X_{t-1} h_t),$$

subject to,

$$\frac{D_{t+1}}{R_t} + R_t^k K_t + W_t h_t = D_t + C_t + K_{t+1} - (1-\delta_t)K_t + \frac{\phi}{2}\left(\frac{K_{t+1}}{K_t} - g\right)^2 K_t.$$

Here g is the steady state growth rate of the economy. $\frac{\phi}{2}\left(\frac{K_{t+1}}{K_t} - g\right)^2 K_t$ are the adjustment costs of capital, with $\phi > 0$. Convex adjustment costs of capital are standard in the open economy literature because they prevent capital from instantaneously adjusting to the differences between the international interest rate and the marginal product of capital. Without these costs, the ultimate implication would be that investment is too volatile, and a counterfactual behavior of trade balance would result. The interest rate on foreign debt, D_t, is given by

$$R_t = R^* + \psi_t e^{\left\{\frac{\tilde{D}_{t+1}}{X_t d} - 1\right\}}.$$

Here R^* is the international gross real interest rate, which is typically associated with the risk free rate. The second term in the right side of the equation is an endogenous spread that depends on the aggregate level of foreign debt $\tilde{D}_t$ with d as the steady state level of foreign debt in effective units and X_t the non-stationary productivity shock discussed before.[7] Following Greenwood et al. (1988) and Garcia-Cicco et al. (2010), I specify the following utility function that is commonly used in the open economy literature

$$u(C_t, X_{t-1} h_t) = \frac{\left(C_t - \theta\omega^{-1} X_{t-1}(h_t)^{\omega}\right)^{1-\sigma}}{1-\sigma}.$$

The setup presented so far, implies a normalized trade balance that can be defined in the following two ways

$$tb_t = y_t - c_t - i_t,$$

or

$$tb_t = d_t - \frac{d_{t+1} g_t}{R_t} - (1-\alpha_t) y_t \left[\frac{\kappa_t(R_t - 1)}{1 + \kappa_t(R_t - 1)}\right],$$

where

$$i_t = k_{t+1} g_t - (1-\delta_t) k_t + \frac{\phi}{2}\left(\frac{k_{t+1}}{k_t} g_t - g\right)^2 k_t.$$

As can be seen, the small open economy assumption simplifies the role of the rest of the world as a provider of funds for consumption smoothing. Hence, no definition of a foreign demand is required. Trade balance to output ratios are central to emerging markets literature as this aggregate experiences strong reversals during macroeconomics crisis. Additionally, note the term $(1-\alpha_t) y_t \left[\frac{\kappa_t(R_t-1)}{1+\kappa_t(R_t-1)}\right]$ which is related to the working capital constraint.

2.3. Introducing parameter instabilities

I allow ψ_t, κ_t, δ_t and α_t to be time-varying. For simplicity, I assume that these parameters follow autoregressive stochastic processes of order one:

$$\log \psi_t = \left(1-\rho_\psi\right)\log \psi + \rho_\psi \log \psi_{t-1} + \sigma_\psi \epsilon_{\psi,t},$$
$$\log \delta_t = (1-\rho_\delta)\log \delta + \rho_\delta \log \delta_{t-1} + \sigma_\delta \epsilon_{\delta,t},$$
$$\log \alpha_t = (1-\rho_\alpha)\log \alpha + \rho_\alpha \log \alpha_{t-1} + \sigma_\alpha \epsilon_{\alpha,t},$$
$$\log \kappa_t = (1-\rho_\kappa)\log \kappa + \rho_\kappa \log \kappa_{t-1} + \sigma_\kappa \epsilon_{\kappa,t}.$$

I assume that all processes are mean reverting and the innovations are standard normal. This is a convenient assumption to have a well-defined steady state to solve the model using a linear approximation. The stochastic processes are specified in logarithms to guarantee that the parameters take only non-negative values.[8] Given the setup of the firms' and households' problems, the time-varying parameters are state variables for the agents' optimization problem.

Additionally, it is clear that there can be multiple sources for parameter changes. Furthermore, this model does not provide an explicit microfoundation for the time variation found in the parameters, and hence, we cannot rule out alternative interpretations of these changes. In Section 4, I study the smoothed estimates of the time-varying parameters to infer which behavior they model.

Note that I assume ρ, ϕ, σ_a, σ_g, β, σ and ω are constant. The first four parameters are constant because they do not affect decision rules up to first order.[9] Conversely, β, σ and ω are time independent to focus on the potential instabilities that arise from technological and financial sources rather than preferences.

[7] Note that this functional form is slightly different to the one Garcia-Cicco et al. (2010), which would be $R_t = R + \psi_t\left[e^{\{\tilde{D}_{t+1}/X_t - d\}} - 1\right]$, as the second term would be zero in steady state. The reason for this slight modification is in order to ψ_t to have an effect in the linearized dynamics of the model.

[8] I follow Fernández-Villaverde and Rubio-Ramirez (2007) in assuming AR(1) processes for time-varying parameters. The main reason for this assumption is that AR(1) processes are flexible and parsimonious.

[9] Their calibration, however, can significantly affect the model dynamics.

Table 1
Calibrated parameters.

θ	σ	α	δ	ω	R	R^*	g
1	2	0.32	0.1255	1.6	1.085	1.01	1.026

Note: The parameters in this table are set to existing literature and calibrated to match first order moments of the data. Details for each parameter are in the main text. σ, ω, α, and δ are defined in the text. R and R^* denote the steady state of the gross real interest rate and the international interest rate, respectively. g denotes the steady state output growth.

3. Estimation: the case of Argentina

I solve the model using log-linear approximation around the steady state.[10] As discussed previously, the choice of log-linear solution methods is not without a loss of generality as it conditions which parameters are allowed to change. Yet, given that Bayesian model estimation and comparison is at the core of this exercise, it remains a good starting point to study time-varying parameters in emerging economies. The parameters presented in Table 1 are set in line the existing literature and calibrated to match first order moments of the data.

In particular $\sigma, \omega, \alpha, \delta$ and R are from Garcia-Cicco et al. (2010). For θ I follow Aguirre (2011). g is calibrated to match the average growth rate of Argentina over the observed sample which equals 2.6% at annual rate. I calibrate the foreign debt to output ratio, D/Y, to target the average trade balance to output ratio observed in the data of about 2.9% and set R^* to match the average US real rate of 1.01. This calibration implies a $\beta = 0.9704$, which is in line with the one in Garcia-Cicco et al. (2010) and a steady state level of $\psi = 0.075$. I estimate the remaining parameters using Bayesian methods for each of the models with and without time-varying parameters. I use 4 observables, the growth rate of private consumption, γ_t^c, the growth rate of output, γ_t^y, the growth rate of investment, γ_t^i and the trade balance to output ratio ($tby_t = TB_t/Y_t$). The goal is to characterize the posterior distribution of the parameters given the data and prior information,[11]

$$p(\Theta|obs) = \frac{L(obs|\Theta)p(\Theta)}{p(obs)} \propto L(obs|\Theta)p(\Theta).$$

Here $p(\Theta|obs)$ is the posterior density of parameters conditional on the observed data, $L(obs|\Theta)$ is the probability that the observed data have been generated by the set of parameters given by Θ, while $p(\Theta)$ stands for the prior distribution that summarizes econometricians' beliefs concerning the unknown parameters and $p(obs)$ is the marginal likelihood given by

$$p(obs) = \int L(\Theta|obs)p(\Theta)d\Theta$$

I assume independent priors for each parameter that follow the distribution specified in Table 2. Here $G(a, b)$ and $B(a, b)$ stand for gamma and beta distributions, respectively, with mean a and standard deviation b. I assume the same priors for standard deviations and autocorrelations of all stochastic processes. As priors are assumed to be independent, the prior distribution, $p(\Theta)$, is given by the product of each parameter's probability distribution function.[12]

Given that the state space is linear and the innovations are normally distributed, we can use the Kalman filter to compute the likelihood function. I maximize the posterior mode and then implement a Random Walk Metropolis-Hastings algorithm, starting from the maximized mode and target a 25% acceptance rate. I use a million draws to evaluate the posterior densities.

Even though most of the procedure is standard, the Metropolis-Hastings algorithm must be modified when working with time-varying parameters because of the parameters' bounds. For example, even though α_t is time dependent, it has to be between 0 and 1 for all t. The same is true for depreciation rates and for the working capital constraint parameter. However, ψ_t is required to be positive for all t. For this reason, for each draw of the Metropolis-Hastings algorithm, after evaluating $L(obs|\Theta)$ I compute smoothed paths for α_t, κ_t, δ_t, ψ_t, using smoothed Kalman filter. I discard the draws that imply that smoothed estimates of these parameters violate their bounds for any t.[13]

Table 3 reports the point estimates and 90% credible sets for two versions of the previous model, one with time-varying parameters and another one with time-invariant parameters. The first main feature seen in the table is that the data strongly favors the model with time-varying parameters as seen by the log marginal likelihood. The posterior odds implied by these estimates is about e^{83}, suggesting a close to zero probability that the data has been generated by the model with time-invariant parameters. In other words, the data suggest the model with time-invariant parameters is over-simplistic.[14] Additionally, the table shows the point estimates and 90% credible sets for each estimated parameter. As seen in the table, specifying the model without parameter drifts slightly distorts point estimates although credible sets overlap. Specifically, the model with time-invariant parameters underestimates the adjustment costs of capital and the working capital constraint. However, in all the cases the parameter estimates are in line with the findings in the existing literature.

As seen, using annual data, all time-varying parameters are highly persistent and substantially volatile; in particular, the estimated variability of these shocks is substantially larger than the ones of technology shocks, suggesting that for the simple real business cycle model, time variation in the parameters might play a substantive role in capturing the characteristics of the data. A key implication of the estimation results of the time-varying simple small open economy model is that the degree of financial frictions experienced by emerging economies exhibits a strong time variation.[15]

The empirical strategy aims at maximizing the likelihood function, that is, it does not target any specific moment of the data, but instead, tries to find the better fit for the whole information contained in the sample. Hence, there is no guarantee the ergodic moments of the model are in line with the sample moments, for this reason, another

[10] Log-linear approximations are commonly used in open macroeconomics literature; here I follow the approach in Schmitt-Grohé and Uribe (2004).

[11] For details on Bayesian estimation procedures, see An and Schorfheide (2007).

[12] For the time-varying parameters model, the priors are in Table 2. For the model with time-invariant parameters, I use the same priors for all parameters except for κ where I use slightly looser priors of $B(0.8, 0.08)$.

[13] I use Durbin and Koopman (2002) smoother.

[14] One concern related to this exercise would be that the data might favor the time-varying parameters model because the time-invariant parameter model just has a very small number of driving forces. In order to make sure that this is not the case, the online appendix repeats this same exercise, comparison of time-varying versus time-invariant parameters model, using the model in Garcia-Cicco et al. (2010) as a baseline. This model includes, on top of permanent and transitory technology shocks, shocks to the interest rate, preferences and government spending. As seen in the appendix, I find that the data supports the model with time-varying parameters and the pattern of variability of the time-varying parameters is very similar to the one captured by the simple model in this section.

[15] The models include also measurements errors (m.e.). In the time-varying parameters model, the maximization of the posterior mode implies that the m.e. for all the observables except the growth rate of investment approach 0. Hence, I set them to the values that maximize the posterior mode such that they do not affect the acceptance rates and the estimation of the remaining parameters. In the case of the time-invariant parameters model, for the same reasons, I do the same for the variances of the m.e. of the growth rate of output.

Table 2
Prior distributions for the time-varying parameters model.

ϕ	κ	ρ_x	σ_x^2
G(1, 0.5)	B(0.9, 0.06)	B(0.75, 0.07)	G(0.15, 0.12)

Note: ρ_x and σ_x^2 are a generic notation to denote persistence and variance for each shock, $x = \{g, A, \delta, \alpha, \kappa, \psi\}$. $G(a, b)$ and $B(a, b)$ stand for gamma and beta distributions, respectively, with mean a and standard deviation b. The estimation also allows for measurement errors and assume $G(0.05, 0.05)$ priors for their variance.

way of "testing" the model is by looking at these moments, which are shown in Table 4.

As seen in the table, both models do a reasonable job in terms of second order moments, however, the model with time-varying parameters is better in all dimensions. In sum, both the log marginal likelihood and the second order moments suggest the model with time-varying parameters is a better fit of the data. A natural question that emerges is what behavior does the time-varying parameters model. A way to answer this question is by looking at the smoothed estimates of these unobserved variables, which I do in the following section.

4. Technology, parameters and the real exchange rate

The previous section shows that the data favor the model with time-varying parameters compared to the model with time-invariant parameters. This section studies the smoothed estimates of time-varying parameters and technology shocks to understand the way the model accommodates to fit the data. I first study the behavior of technology shocks and time-varying parameters and show they seem to experience dramatic changes during currency crisis times and, consequently, I study the co-movement of time-varying parameters with the real exchange rate.

Fig. 1 shows the smoothed estimates of technology shocks. As seen in the figure, the variability of both the permanent and the stationary shocks has been substantially large during the last 70 years, with particularly large deviations during the 1940s, 1970s, 1990s and the debt crisis in 2002 coincidentally with periods of macroeconomic distress and

Table 3
Posterior distributions.

Parameters	Time-invariant parameters			Time-varying parameters		
	Median	5%	95%	Median	5%	95%
ϕ	1.8	1.4	2.4	3.4	2.5	4.5
κ	0.24	0.19	0.29	0.46	0.43	0.48
ρ_g	0.8	0.74	0.86	0.76	0.62	0.86
ρ_z	0.71	0.63	0.78	0.77	0.68	0.84
σ_g	0.042	0.034	0.053	0.019	0.0074	0.027
σ_z	0.035	0.03	0.042	0.026	0.022	0.031
ρ_ψ				0.8	0.71	0.88
ρ_κ				0.79	0.73	0.85
ρ_α				0.78	0.66	0.87
ρ_δ				0.83	0.71	0.92
σ_ψ				0.58	0.5	0.67
σ_κ				0.31	0.26	0.39
σ_α				0.1	0.071	0.14
σ_δ				0.2	0.12	0.28
$\sigma(m.\,e.\,\gamma_c)$	0.025	0.022	0.03			
$\sigma(m.\,e.\,\gamma_i)$	0.095	0.083	0.11	0.028	0.024	0.032
$\sigma(m.\,e.\,tby)$	0.0037	0.001	0.0084			
LML	419.1			502.		

Median, 5% and 95% stand for posterior median, 5th and 95th percentile, respectively. All estimates are computed using the last million draws of the MCMC. LML denotes the log marginal likelihood computed using Geweke's modified harmonic mean with a truncation parameter 0.1 (other truncation parameters generate stable LML). Estimation of $\sigma(m.\,e.\,\gamma_y)$ for the TIP model hits the zero bound, hence I fix it to the values that maximize the posterior mode, $\sigma(m.\,e.\,\gamma_y)^2 = 8.7e^{-7}$. Estimation of $\sigma(m.\,e.\,\gamma_y)$, $\sigma(m.\,e.\,\gamma_c)$ and $\sigma(m.\,e.\,tby)$ for the TVP model hits the zero bound, hence I fix them to the values that maximize the posterior mode, $\sigma(m.\,e.\,\gamma_y)^2 = 1.3e^{-7}$, $\sigma(m.\,e.\,\gamma_c)^2 = 2.6e^{-7}$ and $\sigma(m.\,e.\,tby)^2 = 3.9e^{-8}$.

Table 4
Second order moments.

Moments	Data (SE)	TIP model	TVP model
$\sigma(\gamma_y)$	5.2 (0.59)	8.7	5.7
$\sigma(\gamma_c)$	6.4 (0.72)	8.8	6.6
$\sigma(\gamma_i)$	15.3 (1.6)	13.6	14.6
$\sigma(tby)$	4 (0.46)	4.2	3.3
$\rho(tby, \gamma_y)$	−0.1 (0.01)	−0.26	−0.1
$\rho(tby, \gamma_c)$	−0.3 (0.04)	−0.34	−0.2
$\rho(tby, \gamma_i)$	−0.01 (0.001)	−0.3	−0.3
$\rho(\gamma_y, \gamma_{y,-1})$	0.1 (0.01)	0.18	0.1
$\rho(\gamma_c, \gamma_{c,-1})$	0.001 (0.001)	0.14	0.01
$\rho(\gamma_i, \gamma_{i,-1})$	0.25 (0.03)	−0.05	−0.1
$\rho(tby, tby_{-1})$	0.7 (0.08)	0.77	0.5

Note: I use raw data to compute empirical moments while moments from the model are theoretical. $\sigma(x)$, $\rho(tby, x)$ and $\rho(x, x_{-1})$ denote the volatility of x, the correlation of x with the trade balance to output ratio and the first order autocorrelation of x, respectively. Volatilities are in percentage terms.

policy changes: these shocks are highly volatile, with negative realizations associated to macroeconomic crisis while the opposite occurs during the expansion.

Fig. 2 plots the time-varying parameters in log deviations from steady state in blue dotted lines together with the log real exchange rate in green lines and Table 5 computes the correlation between these same variables.[16] As seen in the figure, strong changes in the real exchange rate are reflected in the time-varying parameters dynamics. For instance, all time-varying parameters substantially increase during the real devaluation following the 2001 crisis and, moreover, they exhibit large swings during the episodes of the late 40s and 70s. Additionally, for the cases of κ_t and ψ_t the co-movement is also observed in the depreciation of the late 80s. More formally, I study first the correlation between smoothed estimates of time-varying parameters and the real exchange rate and then I implement a principal components analysis.

As seen in Table 5, α_t and ψ_t exhibit the largest correlation with the real exchange rate over all the sample in the rage of 0.27 to 0.37, while κ_t and δ_t correlations are milder. However, as seen in Table 6, correlations in the subsample 1936–1979 and 1980–2006 are substantially larger in absolute values. Specifically, following the dramatic appreciation in the late 70s, correlations range from 0.32 to 0.74 for the case of κ_t.[17]

A tool to inquire whether the smoothed estimates of time-varying parameters contain information about the real exchange rate is the principal components analysis (PCA). This tool extracts a set of orthogonal factors that are likely to generate the variability of a dataset. We implement this exercise for a standardized dataset that contains the log real exchange rate, and log deviations of δ_t, α_t, ψ_t and κ_t and a second dataset without the log real exchange rate. Table 7 presents the first 4 principal components for these exercises. The columns $\frac{CV}{TV}$ indicate the share of cumulative variance in terms of total variance explained by all the principal components in each case. As seen in the table, there is a strong correlation between the main principal components and the real exchange rate for all specifications of the exercise. For instance, if the dataset includes the real exchange rate, the first principal component explains about 39% of the variability of the data and has a correlation of about 0.6 with the real exchange rate while the second principal

[16] The real exchange rate is defined as the nominal exchange rate with respect to the US dollar times the US GDP deflator divided by the Argentinean GDP deflator (both base 100 in 1993). Similar dynamics are observed when using the Consumer Price Index to define the bilateral real exchange rate. The correlation between these measures is 98%, however, the CPI real exchange rate is 15% more volatile than the GDP deflator real exchange rate.

[17] At this stage, the model clearly does not provide any fundamental reason for these correlations. This is the case because time-varying parameters in this model act as wedges that change exogenously. Hence, this evidence points out a hidden statistical relationship between several wedges of the model and the real exchange rate. Later I will specify a fully micro-funded model that provides economic meaning to these correlations.

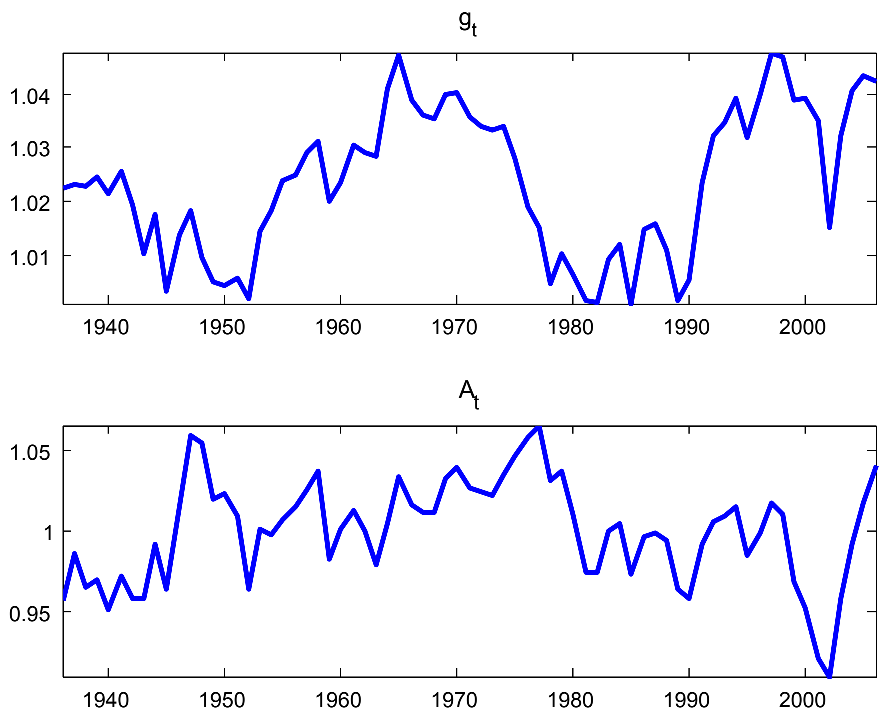

Fig. 1. Smoothed estimates of technology shocks. Note: Smoothed series implied by the model and data and computed using (Durbin and Koopman, 2002) filter.

component, that explains and additional 33% of the variability of the data has a correlation of 0.3 with the real exchange rate. The third principal component basically captures the behavior of the real exchange rate.

The last 2 columns of the table report the results of principal components analysis using a dataset that does not include the real exchange rate. Hence, any information about the real exchange rate in this dataset is only contained in the smoothed estimates of the time-varying parameters (that have been obtained without using the real exchange rate in any step). As seen in the table, even in this case, the principal components have a strong correlation with the real exchange rate. Specifically, the first 2 principal orthogonal components that explain over 80% of the variability of the dataset, have correlations between 0.23 and 0.28 with the real exchange rate. While the fourth component has a correlation

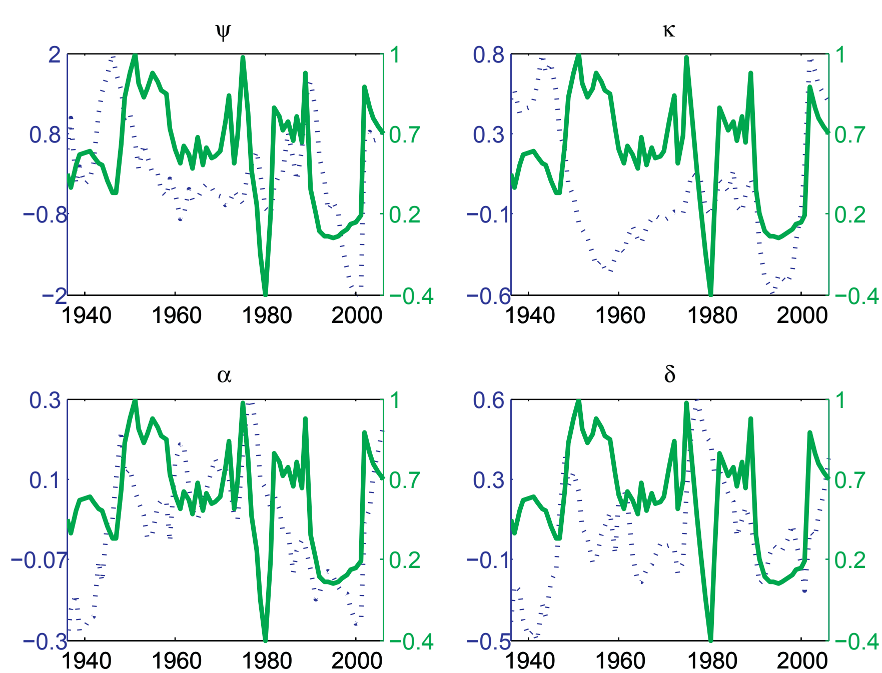

Fig. 2. Smoothed parameters and the real exchange rate. Note: Smoothed series (dotted blue lines) of time-varying parameters are measured on the left hand side axis. The real exchange rate (solid green lines) is measured in the right hand side axis. All variables are in logarithms.

Table 5
Correlation between smoothed estimates and real exchange rate.

	Logs	HP cycle	HP trend
$\rho(rer_t, \psi_t)$	0.27 (0.049)	0.15 (0.03)	0.29 (0.037)
$\rho(rer_t, \kappa_t)$	0.13 (0.02)	0.28 (0.033)	0.032 (0.011)
$\rho(rer_t, \alpha_t)$	0.37 (0.041)	0.075 (0.009)	0.4 (0.046)
$\rho(rer_t, \delta_t)$	0.1 (0.015)	0.1 (0.0063)	0.17 (0.02)

Note: $\rho(x, y)$ denotes the contemporaneous correlation between the log of x and log deviation of y. Standard errors computed by GMM are in parentheses. Cycle and trend denote the cyclical and trend components computed by HP filter with smoothing parameter of 100.

Table 6
Correlation between smoothed estimates and real exchange rate (sub-samples).

	1936–1979	1980–2006
$\rho(rer_t, \psi_t)$	−0.2 (0.04)	0.59 (0.09)
$\rho(rer_t, \kappa_t)$	−0.48 (0.07)	0.74 (0.12)
$\rho(rer_t, \alpha_t)$	0.14 (0.02)	0.53 (0.1)
$\rho(rer_t, \delta_t)$	0.1 (0.02)	0.32 (0.06)

Note: $\rho(x, y)$ denotes the contemporaneous correlation between variables x and y. Standard errors computed by GMM are in parentheses. Cycle and trend denote the cyclical and trend components computed by HP filter with smoothing parameter of 100.

of 0.3. I interpret these correlations as information about the real exchange rate contained in the dataset of only smoothed time-varying parameters.

From these exercises it is clear that the time-varying parameters contain relevant information regarding the behavior of the real exchange rate which cannot be captured by the one-sector model. The relevance and the co-variation of time-varying parameters suggest that the real exchange rate adjustment might be associated with important transmission mechanisms that are absent in the standard one-sector real business cycle model. A natural question is whether Argentina is a special case in the emerging economies for which the real exchange rate is an important variable. To answer this question, the next section provides evidence on the cases of Chile and Mexico.

4.1. Is Argentina special? The cases of Chile and Mexico

This section estimates the time-varying parameters model using data for Chile and Mexico and uses the smoothed estimates of time-varying parameters in each case to study correlations with the real exchange rate and PCA.[18] As seen in this section, the cases of Mexico and Chile also suggest that the behavior of the real exchange rate is key.

Table 8 presents the correlations between real exchange rate and the smoothed estimates of time-varying parameters for Chile and Mexico. As seen in the table, in both cases, the real exchange rate correlates with κ_t, ψ_t and α_t at levels and different frequencies. The bottom line of this table is that, even though the correlation of the real exchange rate with the time-varying parameters varies by country, in all the cases, there seems to be information about the real exchange rate contained in the smoothed estimates of the unobserved parameters. This is also reflected in Table 9 that presents the principal components analysis for each of these economies. Notice that for the case of Chile, when the real exchange rate is included in the dataset, the first component has a correlation of 0.64 with the real exchange rate and the second principal component has a strong negative correlation. Also when the real exchange rate is not included, the first three principal components strongly correlate with the real exchange rate. For the case of Mexico, the first principal component tends to be the most correlated with the real exchange rate when this variable is part of the dataset, and the third component has a very strong correlation with the real exchange rate when this variable is not in the dataset.

This section has shown that there is strong evidence suggesting the one-sector model is severely misspecified when studying emerging market. First, the data supports the time-varying parameters model, second, the smoothed estimates of these time-varying parameters are strongly correlated with the real exchange rate and actually, principal component analysis suggests these smoothed estimates contain information about the real exchange rate when we do not model it explicitly. Third, this is the case for various emerging economies.

[18] Additional results for these exercises are available in the online appendix while this section only reports the correlation of smoothed estimates of time-varying parameters and the principal component analysis.

Economically, the intuition why the dynamics of these economies depend on the real exchange rate is simple. Emerging economies issue debt in foreign currency, domestic production depends on imported inputs, and a substantial share of domestic income comes from exporting goods to the rest of the world. All these links imply that changes in the relative price of domestic goods in terms of foreign goods are likely to have important income and substitution effects that are absent in the one-sector model. In the next section, I introduce a model that explicitly takes these links into account.

5. A two-sector model with financial frictions

The evidence presented in the previous sections shows that the data favors the time-varying parameter model over the state of the art small open economy model when applied to emerging economies. When inquiring about the source of time-varying parameters' variability, we found strong evidence suggesting that the real exchange rate plays an important role. This section introduces a two-sector model, with tradable and non-tradable goods, that explicitly takes into account the behavior of the real exchange rate.

The two-sector model endogenizes the time-varying parameters of the baseline one-sector model. First, this model introduces differentiated capital utilization rates that affect capital depreciation rates in both the tradable and non-tradable sectors over time, implying ultimately endogenous time-varying capital depreciation rates. Second, I allow for differentiated working capital constraints among tradable and non-tradable producers in a way that sectoral relocation would resemble the time-varying working capital constraint intensity and capital shares. These modeling choices are introduced with the objective of capturing the reduced form dynamics identified in the one-sector model and to allow the model to capture the fact that sectoral relocation when real exchange rates move is costly.

5.1. Households

I assume that households maximize the present value of expected utility defined over an aggregate consumption bundle and leisure,

$$\max\ \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(C_t, X_{t-1} h_t),$$

Table 7
Principal component analysis.

	Standardized		Standardized - Excluding RER	
	$\frac{CV}{TV}$	$\rho(pc, rer)$	$\frac{CV}{TV}$	$\rho(pc, rer)$
PC1	39	0.57 (0.06)	45	0.23 (0.05)
PC2	72	0.30 (0.06)	83	0.28 (0.06)
PC3	88	0.76 (0.08)	94	-0.1 (0.03)
PC4	96	−0.07 (0.03)	100	0.31 (0.04)

Note: $\frac{CV}{TV}$ computes the cumulative variance to total variance ratio. $\rho(pc, rer)$ denotes the contemporaneous correlation between the principal component and the real exchange rate with standard errors in parentheses. Variance shares are in percentage terms. “Standardized” computes PCA standardizing the data. “Excluding RER” computes standardized PCA without including the real exchange rate in the dataset.

Table 8
Correlation between smoothed estimates and real exchange rate.

	Chile			Mexico		
	Logs	Cycle	Trend	Logs	Cycle	Trend
$\rho(rer_t, \psi_t)$	−0.53 (0.07)	−0.01 (0.03)	−0.65 (0.07)	0.43 (0.06)	0.47 (0.07)	0.19 (0.03)
$\rho(rer_t, \kappa_t)$	0.5 (0.06)	0.43 (0.06)	0.41 (0.05)	0.27 (0.04)	0.34 (0.05)	0.16 (0.02)
$\rho(rer_t, \alpha_t)$	0.34 (0.05)	0.13 (0.02)	0.35 (0.05)	−0.2 (0.03)	−0.05 (0.01)	−0.22 (0.03)
$\rho(rer_t, \delta_t)$	0.04 (0.01)	0.035 (0.04)	0.24 (0.03)	−0.26 (0.04)	−0.26 (0.003)	−0.31 (0.04)

Note: $\rho(x, y)$ denotes the contemporaneous correlation between variables x and y. Standard errors computed by GMM are in parentheses. Cycle and trend denote the cyclical and trend components computed by HP filter with smoothing parameter of 100.

subject to a sequence of budget constraints,

$$\frac{D_{t+1}}{R_t} - D_t = p_t^c C_t + I_t^N + I_t^T - w_t h_t - r_t^N u_t^N K_t^N - r_t^T u_t^T K_t^T.$$

Here, h_t denotes labor supply, and C_t is a consumption aggregator of tradable and non-tradable consumption goods, given by

$$C_t = \left[\gamma^T \left(C_t^T\right)^{\frac{\theta-1}{\theta}} + \gamma^N \left(C_t^N\right)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}},$$

with p_t^c being the price of consumption goods in terms of tradable goods.[19]

Here, u_t^N and u_t^T are the utilization rates of capital in the non-tradable and the tradable goods production sectors, respectively. I allow households to accumulate and rent utilized capital allocated to non-tradable goods production and tradable goods production. Capital accumulation and depreciation rates for $j = \{T, N\}$ evolve according to

$$K_{t+1}^j = \left(1 - \delta\left(u_t^j\right)\right) K_t^j + I_t^j - \frac{\phi^j}{2}\left(\frac{K_{t+1}^j}{K_t^j} - g\right)^2 K_t^j,$$
$$\delta\left(u_t^j\right) = \delta^j + \Phi_1\left(u_t^j - 1\right) + \frac{\phi_2^j}{2}\left(u_t^j - 1\right)^2.$$

In this problem, households solve an intratemporal problem between consumption of tradable and non-tradable goods, on top of the standard leisure-consumption problem, and an intertemporal problem where households choose consumption and savings using foreign debt and capital in the tradable and non-tradable sector. Additionally, households choose utilization of capital in each sector.[20]

5.2. Firms

As in the one-sector model, firms rent capital and labor from households at given prices to maximize profits.

$$\Pi_t^f = \sum_{j=N,T} p_t^j Y_t^j - r_t^j K_t^{s,j} - \eta^j (R_t - 1) W_t h_t^j - W_t h_t^j.$$

I assume they produce two types of goods, tradable goods that can be used for consumption, investment or traded internationally and non-tradable goods that can only be consumed domestically. Firms operate according to a Cobb–Douglas technology

$$Y_t^j = A_t^j \left(K_t^{s,j}\right)^{\alpha_j} \left(X_t h_t^j\right)^{1-\alpha_j}.$$

for $j = \{T, N\}$. Here $K_t^{s,j}$ are the total capital services demanded by firms. X_t denotes the non-stationary technology shock that follows the same process as in the baseline model. As opposed to the one-sector model, I assume there are two independent shocks to the total factor productivity in the tradable and non-tradable sectors. Transitory technological shocks are given by

$$\log A_t^T = (1 - \rho_{A,T}) \log A^T + \rho_{A,T} \log A_{t-1}^T + \epsilon_{T,t},$$
$$\log A_t^N = (1 - \rho_{A,N}) \log A^N + \rho_{A,N} \log A_{t-1}^N + \epsilon_{N,t}.$$

Additionally, firms are subject to two working capital constraints that might have different elasticities to account for the time variation in the tightness of working capital constraint in the previous section. Finally, I model the domestic interest rate in a similar manner as that found in the previous section,

$$R_t = R + \psi e^{\{\tilde{D}_{t+1}/X_t - d\}} + e^{\xi_t - 1} - 1.$$
$$\log \xi_t = \rho^{\xi} \log \xi_{t-1} + e_{\xi,t}.$$

ξ_t is an interest rate shock that accounts for a multiplicity of foreign shocks, such as contagion effects from other emerging economies and shocks to world economic conditions and financial frictions in world asset markets, as discussed in Garcia-Cicco et al. (2010).[21]

5.3. Estimation

I estimate this model using data for the growth rates of output, consumption and investment; the trade balance to output ratio and the logarithm of the real exchange rate. Given that the real exchange rate in the data is defined as the nominal exchange rate times the US GDP deflator (base year 1993) divided by the Argentina GDP deflator (base year 1993), I define the real exchange rate in the model as $rer_t = 1/p_t^c$, which is the price of tradable goods in terms of the price of the domestic consumption bundle. Hence, all aggregates in the data are in terms of Argentina GDP deflator, meaning that all aggregates in the model have to be expressed in terms of consumption prices. Hence, the consumption aggregate in the model that maps the one in the data is c_t, the investment aggregate in the model that maps the one in the data is $i_t = \frac{i_t^N + i_t^T}{p_t^c}$ and the model counterpart of output is $y_t = \frac{y_t^T + p_t^N y_t^N}{p_t^c}$. Finally, the trade balance to output ratio would be defined as $tby_t = \frac{TB_t/p_t^c}{y_t}$.

Table 10 shows the parametrization for the non-estimated parameters. $\sigma, \omega, R, g, R^*$ and $\psi = R - R^*$ are set as in the one-sector model. The real exchange rate in steady state is set to match the sample average and the debt to output ratio is calibrated to match the average trade balance to output ratio observed in the data. I fix δ^N and δ^T to 0.1255, the same depreciation rate of the one-sector model and $\gamma^T = 0.5$ as in Uribe and Schmitt-Grohé (2015). I set $\alpha^N = \alpha^T = 0.25$ and the average transitory technology shock in the tradable sector is fixed to 1. Average

[19] The price of consumption goods is implicitly defined by $p_t^c C_t = C_t^T + p_t^N C_t^N$. Under these conditions, the intratemporal allocation problem between tradable and non-tradable consumption gives
$C_t^T = (\gamma^T)^{\theta} (\frac{1}{p_t^c})^{-\theta} C_t \quad C_t^N = (\gamma^N)^{\theta} (\frac{p_t^N}{p_t^c})^{-\theta} C_t, \quad p_t^c = [(\gamma^T)^{\theta} + (\gamma^N)^{\theta} (p_t^N)^{1-\theta}]^{\frac{1}{1-\theta}}$.

[20] The online appendix presents a detailed derivation of the optimality conditions.

[21] Note that in the linear approximation, ξ_t in this model plays the same role as ψ_t in the one sector time-varying parameter model.

Table 9
Principal component analysis (PCA).

	Chile				Mexico			
	Standardized		Excluding RER		Standardized		Excluding RER	
	$\frac{CV}{TV}$	$\rho(pc, rer)$	$\frac{CV}{TV}$	$\rho(pc, rer)$	$\frac{CV}{TV}$	$\rho(pc, rer)$	$\frac{CV}{TV}$	$\rho(pc, rer)$
PC1	47	0.64 (0.07)	53	0.35 (0.05)	49	−0.35 (0.05)	60	−0.19 (0.03)
PC2	76	−0.62 (0.07)	81	−0.4 (0.05)	79	0.79 (0.11)	86	0.49 (0.07)
PC3	94	−0.36 (0.05)	97	−0.57 (0.07)	91	−0.37 (0.05)	98	−0.20 (0.03)
PC4	98	−0.26 (0.03)	100	0.21 (0.03)	99	−0.34 (0.05)	100	−0.06 (0.08)

Note: $\frac{CV}{TV}$ computes the cumulative variance to total variance ratio. $\rho(pc, rer)$ denotes the contemporaneous correlation between the principal component and the real exchange rate with standard errors in parentheses. Variance shares are in percentage terms. "Standardized" computes PCA standardizing the data. "Excluding RER" computes standardized PCA without including the real exchange rate in the dataset.

Table 10
Fixed parameter values.

σ	γ^T	α^N	α^T	δ^N	δ^T	ω	g	R	R^*	Log(RER)
2	0.50	0.25	0.25	0.1255	0.1255	1.6	1.026	1.085	1.01	0.57

Note: This table shows the parametrization of non-estimated parameters that are set to those in the existing literature and calibrated to match first order moments of the data. Details are in the main text.

transitory technology shock in the non-tradable sector and θ is obtained from the steady state conditions such that $z_N = 4.97$ and $\theta = 2.94$. We fix $\phi_2^T = 20$ given that the estimation does not seem to identify it properly and as it is common I fix utilization rates to 1 in steady state, which imply that $\phi_1^T = 0.21$ and $\phi_1^N = 0.21$ are obtained from the steady state conditions.

The remainder of the parameters in the model are estimated following the same strategy as with the one-sector model. The prior distributions for the two-sector model are shown in Table 11. As in the one-sector model, this section allows for measurement errors in the estimation.

Table 12 presents point estimates and credible sets for the two-sector model. As seen in the Table, the data highlights some differences and similarities among the tradable and non-trabable sectors. From the estimates, it seems that the costs of operating the non-tradable sector are slightly larger than those of operating in the tradable sector, as can be seen by the larger η^N and ϕ^N. However, the volatility of the innovation to the tradable sector is much larger than the one in the non-tradable sector while the average technology level is 1/4 of the non-tradable counterpart. Explaining the dynamics of the real exchange rate without disrupting the behavior of aggregate demand components is a challenge as the variability of this variable is almost 10 times larger than the variability of output growth, this is attained by the relocation costs of moving resources between sectors. Next section studies the dynamic properties of the model and implements a variance decomposition to see the relative importance of different shocks.

5.4. Accounting for real exchange rate variability

Table 13 shows that the model is able to generate real exchange rate dynamics of the order of magnitude and co-movement with national account aggregates as the ones observed in the data. For instance, the real exchange rate volatility generated by the model is 37.8%, in line with the one in the data. Moreover, the model captures the negative correlation of the real exchange rate with output, investment and consumption growth observed in the data.

For comparison purposes, the table includes the moments implied by the baseline model with and without time-varying parameters. Note that compared to the time-invariant parameter one-sector model, the two-sector model improves the aggregate dynamics in several dimensions both in terms of variability and co-movement. For instance, the two-sector model overall improves the volatility of all observables taking into account that it generates a sizable variability of the new observable, the real exchange rate. It improves the co-movement of trade balance to output ratio with output and investment growth. On top of this, the model generates the co-movement of the real exchange rate with output, consumption and investment growth. Instead, compared to the time-varying one-sector model, the two-sector model generates a slightly larger output volatility but has a similar performance on most of the shared observables.

Another way to evaluate the performance of this model in absolute terms is by using the *posterior predictive densities*.[22] When estimating a model using maximum likelihood, the shocks of the model accommodate to deliver the best possible fit, even if measurement errors are included. Once posterior estimates are available, a reasonable question to ask is how plausible the dynamics of the shocks are. However, this question raises a problem given that the shocks are not observed. Posterior predictive densities provide a way to deal with this issue by simulating the model over artificial datasets. In particular, the moments of interest are computed using artificial datasets for different draws of the Metropolis-Hastings. If we repeat this step several times, we can construct a distribution for different moments and we can use these distributions to compare the smoothed moments obtained by filtering the data through the model and then smoothing the dynamics using Kalman filter. The objective is then to assess how plausible the smoothed moments are, when compared to the artificial series created by the model. Fig. 3 presents the results of this exercise for several key moments related to the real exchange rate.

The figure shows several moments of interest related to the real exchange variable and its co-movement with all other observables. The figure plots the posterior densities together with the moments observed in the data and the moments implied by the smoothed counterpart of the observables obtained by Kalman smoother. First notice that these two set of moments are usually very similar, which is due to the good fitting of the model and the use of measurement errors. Second, as seen in the figure, the model does a good job in fitting the volatility of the real exchange rate and its correlation with investment growth and

[22] Posterior odds evaluates the performance of a model in a relative term as it compares different models using the same data set. This exercise will not be particularly useful in our case as the one-sector model does not include a real exchange rate, which is key for the two-sector model.

Table 11
Prior distributions.

ϕ^N	ϕ_2^T	ϕ^T	κ^j	ρ_x	σ_x^2	h^T/h
$N_+(20, 5)$	$N_+(20, 5)$	$N_+(20, 5)$	B(0.7, 0.13)	B(0.7, 0.10)	G(0.06, 0.05)	B(0.5, 0.15)

Note: ρ_x and σ_x^2 denote persistence and variance for each shock. $G(a, b)$, $B(a, b)$ and $N_+(a, b)$ stand for gamma, beta and normal distributions, respectively, with mean a and standard deviation b, and in the case of the normal distribution, it is truncated to allow only for positive values. The estimation also allows for measurement errors and assume $G(0.01, 0.01)$ priors for their variance.

its autocorrelation. Even though the model seems to have a hard time in getting other moments such us the correlations with output and consumption growth, in all the cases, a substantially large mass of the posterior densities of these moments is in line with the qualitative behavior observed in the data and to a similar order of magnitude. In other words, the model has a significant probability of generating the variability and co-movement of the real exchange rate of a similar order to the one observed in the data.

5.5. Variance decomposition

After showing that the model can accurately capture the behavior of the data including the discipline imposed by the real exchange rate, we can use it to learn which shocks matter the most for the variability of the observables. This exercise has been object of controversy as Aguiar and Gopinath (2007) find that trend shocks are the most important driving force in emerging economies while Garcia-Cicco et al. (2010) find that when accounting for financial frictions, the importance of trend shocks is mild. Table 14 presents the variance decomposition of the two-sector model and the different versions of the one-sector model.

It is important to highlight that the message of the variance decomposition exercise for the two-sector model is in line with the one in Garcia-Cicco et al. (2010). The permanent technology shock explains a rather moderate variability of the observables. It is particularly important for output and consumption growth. In the cases of investment growth, the trade balance to output ratio or the real exchange rate of this shock is not a major source of variability. Instead, stationary technology shocks jointly explain about 60% of the variability of output, about 40% of the variability of consumption and 17% of the variability of investment growth. The country premium also plays an important role in some of the cases, in particular related to the growth rate of investment and the trade balance to output ratio. Finally, our findings suggest that the behavior of the real exchange rate is mainly explained by the stationary technology shocks to the tradable sector.

The table also presents the shares of explained variability in the two versions of the one-sector model. Note that in line with Aguiar and Gopinath (2007), in the model with only permanent and transitory shocks, permanent shock generates the largest share of the explained variability in most of the cases. However, when time-varying parameters are considered, the importance of permanent shocks as driving forces of the cycle decreases substantially and it seems that permanent and transitory shocks are equally important. Once the two-sector model is considered, and the endogenous channel of the real exchange rate is explicitly modeled, we see that the variability generated by the transitory technology shocks is substantially larger than the one implied by the one-sector model.

6. Conclusions

This paper reviews the baseline theoretical framework for the analysis of emerging economies, the real business cycle model. I estimate a one-sector small open economy model with trend shocks, working capital constraint and augmented with time-varying parameters that follow AR(1) processes for Argentina, and I find that the smoothed estimates of the time-varying parameters correlate with the real exchange rate at different frequencies and that changes in the time-varying parameters are substantial during corrections of the real exchange rate. This methodology constitutes a novel approach, using the flexibility given by time-varying parameters to show that the real exchange rate matters even when the models include the latest devices proposed in the literature.

Therefore, I propose a two-sector model that accounts for real exchange rate movements and non-tradable goods that include capital utilization rates, differentiated working capital constraints and financial frictions as in Garcia-Cicco et al. (2010). I take this model to the data and

Table 12
Posterior estimates and credible sets for the two-sector model.

Parameters	Median	5pct	95pct
η^N	0.75	0.53	0.91
η^T	0.62	0.37	0.84
ϕ^N	3.2	2.1	5
ϕ^T	1.7	1	3.5
ϕ_2^T	20	12	28
ρ_{z^N}	0.83	0.65	0.93
ρ_{z^T}	0.82	0.75	0.88
ρ_g	0.67	0.54	0.79
ρ_d	0.82	0.73	0.9
ρ_ν	0.88	0.8	0.93
σ_{z^T}	0.23	0.18	0.28
σ_{z^N}	0.022	0.0078	0.031
σ_ξ	0.027	0.021	0.035
σ_g	0.029	0.0098	0.043
σ_ν	0.27	0.21	0.37
h^T/h	0.25	0.23	0.27
$\sigma(m.\ e.\ \gamma_c)$	0.008	0.0068	0.0095
$\sigma(m.\ e.\ \gamma_i)$	0.014	0.0051	0.022
$\sigma(m.\ e.\ log(rer))$	0.091	0.033	0.15

Note: "Median" stands for posterior median and "%" stands for percentiles. Computed using 1 million draws of the Metropolis-Hastings procedure. Estimation of $\sigma(m.\ e.\ \gamma_y)$ and $\sigma(m.\ e.\ \gamma_{tby})$ hits the zero bound, hence I fix them at the values that maximize the posterior mode, $\sigma(m.\ e.\ \gamma_y)^2 = 3.4e^{-7}$ and $\sigma(m.\ e.\ \gamma_{tby})^2 = 2.6e^{-8}$.

Table 13
Second order moments.

Moments	Data (SE)	Two-sector model	TVP model	TIP model
$\sigma(\gamma_y)$	5.2 (0.59)	6.7	5.7	8.7
$\sigma(\gamma_c)$	6.4 (0.72)	7.3	6.6	8.8
$\sigma(\gamma_i)$	15.3 (1.6)	15.2	14.6	13.6
$\sigma(tby)$	4 (0.46)	5.2	3.3	4.2
$\sigma(rer)$	36.5 (3.4)	37.9		
$\rho(tby, \gamma_y)$	−0.08 (0.01)	−0.06	−0.1	−0.26
$\rho(tby, \gamma_c)$	−0.31 (0.04)	−0.26	−0.2	−0.34
$\rho(tby, \gamma_i)$	−0.01 (0.001)	−0.17	−0.3	−0.3
$\rho(tby, rer)$	0.25 (0.03)	−0.06		
$\rho(rer, \gamma_y)$	−0.005 (0.002)	−0.27		
$\rho(rer, \gamma_c)$	−0.12 (0.01)	−0.30		
$\rho(rer, \gamma_i)$	−0.04 (0.01)	−0.03		
$\rho(\gamma_y, \gamma_{y,-1})$	0.10 (0.01)	0.15	0.1	0.18
$\rho(\gamma_c, \gamma_{c,-1})$	0.001 (0.001)	0.08	0.01	0.14
$\rho(\gamma_i, \gamma_{i,-1})$	0.25 (0.03)	−0.09	−0.1	−0.05
$\rho(tby, tby_{-1})$	0.70 (0.08)	0.70	0.5	0.77
$\rho(rer, rer_{-1})$	0.76 (0.08)	0.83		

Note: I use raw data to compute empirical moments while moments from the model are theoretical. $\sigma(x)$, $\rho(tby, x)$ and $\rho(x, x_{-1})$ denote the volatility of x, the correlation of x with the trade balance to output ratio and the first order autocorrelation of x, respectively. Volatilities are in percentage terms.

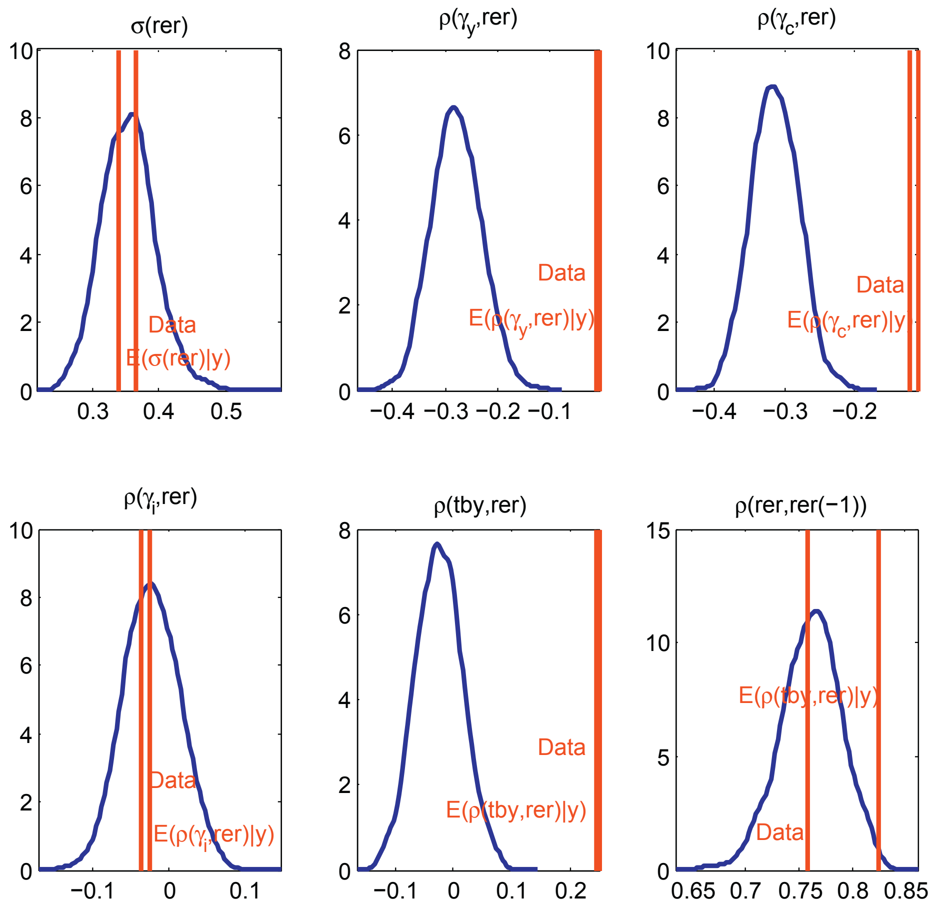

Fig. 3. Predictive posterior densities. Note: Posterior predictive *p*-values computed using 1 every 1000 draws from Metropolis-Hastings and 1000 simulations of the sample sample size of the dataset. $\sigma(x)$ and $\rho(x, rer)$ denote the volatility of *x* and the correlation of *x* with the real exchange rate, respectively. The red vertical lines are the smoothed moments implied by the model and the data.

show that it can successfully account for the most salient stylized facts in emerging economies. I find that the role of trend shocks is relatively mild in accounting for the volatility of observables but the stationary productivity shocks play a major role. This finding is in line with existing literature as shown in Garcia-Cicco et al. (2010).

Table 14
Variance decomposition: a two-sector model.

Shocks	γ^y	γ^c	γ^i	tby	Log(RER)
Two-sector model					
Explained variability	100	99	99	100	95
Transitory non-tradable technology	41	21	15	1.8	1.3
Transitory tradable technology	16	20	1.8	12	98
Spread	3.1	15	46	57	0.21
Preference	3.7	11	23	22	0.87
Permanent technology	36	33	13	6.7	0.01
One-sector model with time-varying parameters					
Permanent technology	17	16	2.9	4.9	
Transitory technology	69	40	17	2.8	
ψ_t	2.8	14	35	72	
κ_t	2.4	6.2	1.2	15	
α_t	2.3	15	26	1.2	
δ_t	6	9.1	19	3.3	
One-sector model with time-invariant parameters					
Permanent technology	46	66	57	94	
Transitory technology	54	34	43	6	

Note: The table reports the shares of explained variability of different observables for each of the three model studied in the paper. Each row presents the shares of variability explained by each shock in percentage of total explained variability.

The main implication of this paper is that the real exchange rate matters both in terms of transmission mechanisms and because considering its behavior endogenously affects the relative importance of driving forces. The two-sector model improves the performance of the business cycle model in several aspects, however, potential directions for further improvement should be explored, including those of labor frictions, monopolistic competition and policy changes. In sum, a possibility for future research would be to review and reconsider whether the standard findings in emerging markets literature hold when the dynamics of the real exchange rate is taken into account.

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